Ecological Economics 149 (2018) 294–305

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Benefits From Water Related Ecosystem Services in Africa and Climate Change

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ARTICLE INFO

JEL Classification:
N57: Africa, Oceania
O13: Agriculture, Natural Resources, Energy, Environment, Other Primary Products
Q57: Ecological Economics: Ecosystem Services, Biodiversity Conservation, Bioeconomics, Industrial Ecology
Q54: Climate, Natural Disasters, Global Warming

Keywords:
Adaptation
Africa
Ecosystem services
Meta-analysis
Natural capital
ND-GAIN
Readiness
Valuation
Vulnerability
Water

ABSTRACT

The present study collects original monetary estimates for water related ecosystem service benefits on the African continent from 36 valuation studies. A database of 178 monetary estimates is constructed to conduct a meta-analysis that, for the first time, digs into what factors drive water related ecosystem service values in Africa. We find that the service type, biome and other socioeconomic variables are significant in explaining benefits from water related services. In order to understand the importance that benefits from water related ecosystem services have for climate change, we explore the relationship between these benefits and the countries' vulnerability and readiness to adapt to climate change. We find that countries face synergies and trade-offs in terms of how valuable their water related ecosystem services are and their potential vulnerability and adaptation capacity. While more vulnerable countries are associated with lower benefits from ecosystem services, countries with a higher readiness to adapt are also associated with lower ecosystem service values. Results are discussed in light of natural capital accounting and ecosystem-based adaptation.

1. Introduction

The concept of ecosystem services (ESs), understood as the contribution of the benefits derived passively or actively from ecosystems towards current and future human well-being (Fisher et al., 2009), has gained increasing recognition in the last decade. Mainstreamed by the Millennium Ecosystem Assessment (MA) Program (2005), ESs were at the focus of the United Nations Environment Programme (UNEP) led study on The Economics of Ecosystems and Biodiversity (TEEB, see de Groot et al., 2012), and are still evolving under the currently developing Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) initiative (Díaz et al., 2015). The conservation and improvement of ecosystems has been identified as a central challenge to sustaining livelihoods for the XXIst century (Gleik et al., 2003; Guerry et al., 2015), and research programs as well as conservation initiatives have been launched at local, national and international levels (Díaz et al., 2015). In this context, research to synthetize available evidence on ES monetary values is of prime importance, and understanding what drives these values and how they relate to countries' climate vulnerability can provide policy guidance regarding the potential of ESs for climate change adaptation.

The present paper focuses on water related ESs in Africa and their links to climate change vulnerability and adaptation. Water-related ESs are understood as the services provided by biomes that are river flow impacting or river flow dependent (see the concept of natural infrastructure in Mul et al., 2017).[1] In other words, biomes that impact or are predominantly dependent on river flow, as opposed to being predominantly rain fed, deliver water related ESs. This landscape approach considers biomes as the entry point to identify the set of ESs produced. The water related ES category draws on the MA and TEEB

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[1] For more on this distinction, please see the WISE UP project http://www.waterandnature.org/initiatives/wise-climate.

https://doi.org/10.1016/j.ecolecon.2018.03.021
Received 10 August 2017; Received in revised form 12 March 2018; Accepted 19 March 2018
Available online 06 April 2018

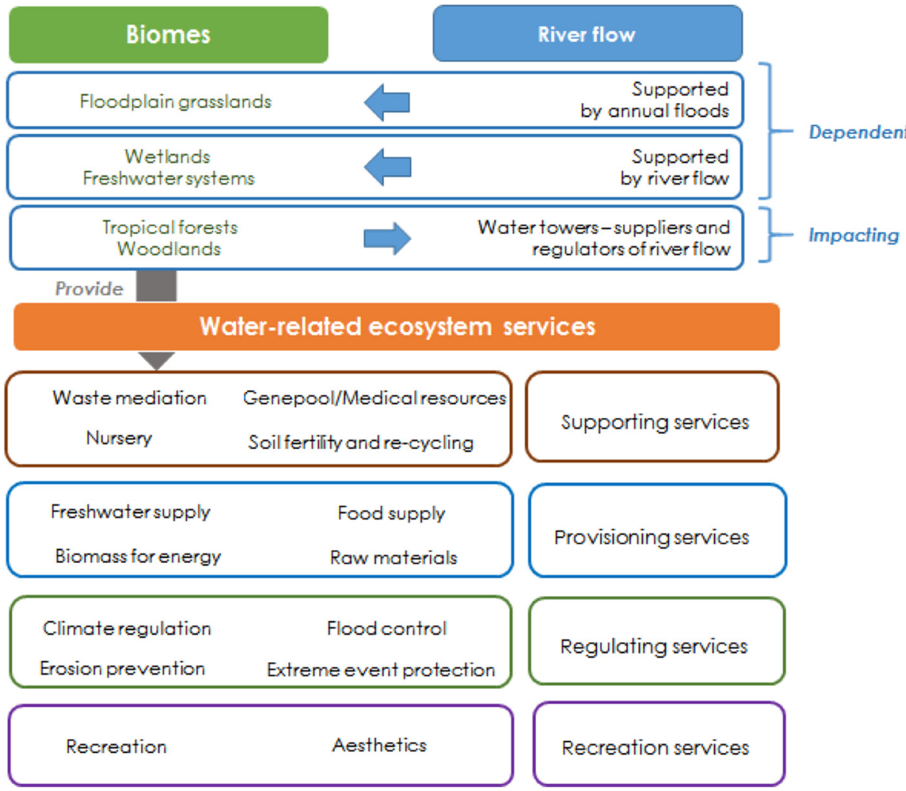

Fig. 1. Water related services from biomes linked to river flows.
Source: adapted from Mul et al. (2017) and the MA (2005).

classifications (MA, 2005; de Groot et al., 2012) and encompasses more ESs than hydrological services (Grizzetti et al., 2016). Fig. 1 presents the biomes included in the present study which interact with surface river flow and provide water related ESs.

Previous research has paid a lot of attention to water related ESs in other regions mainly due to the development of Payment for Ecosystem Services (Lele, 2009), but no previous studies have analyzed the values of water related ESs in relation to climate vulnerability and adaptation. In this paper, the focus is on the African continent, for three main reasons: 1) River flows are pivotal to the delivery of ESs crucial to millions of livelihoods (WWAP, 2016); 2) the African continent presents in general a high climate change vulnerability exacerbating the need for immediate policy solutions (World Bank, 2007), and; 3) water related ESs in Africa continue to be inadequately investigated with very poor coverage (Lele, 2009).

Water related ESs are affected by a very high variability of all climate and water resources characteristics — in turn exacerbated by climate change (Faramarzi et al., 2013; IPCC, 2014). Understanding the benefits of water related services delivery through economic valuation and the factors that affect these economic benefits can provide guidance for water resource management and climate change adaptation.

Africa is not the continent with the largest ES valuation literature (for details on ES valuation methods see de Groot et al., 2012; Pascual et al., 2010). Only 19% of the valuation studies referenced in TEEB are located in Africa. Most studies are located in the Americas (33%) and Asia (26%) (based on Mc Vittie and Hussain, 2013). Moreover, the valuation literature in Africa is geographically disparate: Southern and Eastern Africa gather the highest number of studies while North, West and central sub-Saharan Africa go under-represented. Valuation studies on water related ESs in Africa represent 28% of all water related ES valuation studies globally. The most frequently valued water related ESs are raw materials and food provision, mainly due to two different reasons: 1) these services are relatively easy to value using the direct market pricing method (Van der Ploeg et al., 2010) and; 2) dependence on provisioning services is high and proportionally larger in African developing countries than in developed countries, hence an early focus on estimating values for this type of service (Egoh et al., 2012; Mc Vittie and Hussain, 2013). Indeed, ESs' consumptive outputs (e.g. crops and fish) contribute to subsistence livelihoods and constitute a very important share of households' income in African developing countries, thus participating in poverty alleviation and reducing vulnerability to negative shocks (Egoh et al., 2012; Suich et al., 2015).

The role of ESs in reducing vulnerability and in contributing to adaptation is particularly important in the face of climate change (Jones et al., 2012; Munang et al., 2013a). Adaptation to climate change can be rooted in ES sustainability — known as 'ecosystem based adaptation' (Ojea, 2015). It is defined as an approach that "harness the capacity of nature to buffer human communities against the adverse impacts of climate change through the sustainable delivery of ES" and is expected to provide cost-effective adaptation resulting in resilient socio-ecological systems (Jones et al., 2012). Such adaptation option is hailed as particularly beneficial as carbon sequestering ecosystems[2] such as forests, wetlands and peatlands can contribute to achieving mitigation targets set under the 2015 Paris agreement as well as the sustainable development goals of the United Nations while delivering on adaptation to climate change (Munang et al., 2013b). Early evidence on ecosystem based adaptation supports this is the case (Doswald et al., 2014). However, little is known yet on the linkages between adaptation and the value of ESs at a regional scale (Ojea et al., 2015). Indeed, ecosystem-based adaptation approaches have not been mainstreamed yet, with only little evidence in the literature (Jones et al., 2012).

[2] A recent review highlights that much of the claimed climate regulation benefits of EbA, beyond carbon sequestering ecosystems, relate to local temperature regulation rather than mitigation (McVittie et al., 2017).

Indeed, ES valuations are mostly conducted in isolation of climate change and adaptation considerations. To fill this gap, one feasible approach is to explore to what extent water related ES values are related to higher (or lower) vulnerability and higher (or lower) leverage to adapt to climate change in countries. The present paper addresses these questions to explore the potential links between the value of water related ESs and countries' vulnerability and potential to adapt to climate change.

To do this, the paper synthesizes water related ES values elicited for Africa in the last three decades using a meta-analysis. Meta-analyses – the analysis of analyses as defined by Glass (1976) – have been increasingly used in the field of environmental valuation (Brander et al., 2006; Ghermandi et al., 2008) as it allows for a rigorous testing of a central tendency across a large number of studies while controlling for the effect of several parameters (Nelson and Kennedy, 2009). In this context, a meta-analysis for water related ES values is carried out to: 1) provide a quantitative answer to what factors drive water related ES values in Africa and; 2) understand the relationship between climate change vulnerability and readiness to adapt and the benefits obtained from ESs.

The next section introduces the methodology and outlines the data selection, standardization and coding carried out in order to perform the meta-regression. Section 3 presents the model specification and Section 4 its associated results. Section 5 discusses the result implications before the concluding section.

2. Methodology

2.1. Existing Meta-analyses of Water-related ESs

Studies aimed at understanding the benefits from ESs have so far conducted meta-analyses focused on one ecosystem type, such as coral reefs (Brander et al., 2007; Ghermandi and Nunes, 2013), coastal and marine ecosystems (Liu and Stern, 2008), wetlands (Brander et al., 2006; Brouwer et al., 1999; Chaikumbung et al., 2016; Ghermandi et al., 2008; Woodward and Wui, 2001), forests (Barrio and Loureiro, 2010; Ojea et al., 2016), or mangroves (Brander et al., 2012). Other studies focus on one or a bundle of ESs for a specific ecosystem, such as recreational services from forests (Ojea et al., 2015; Zandersen and Tol, 2009); water ESs from forests (Ojea et al., 2015; Ojea and Martin-Ortega, 2015); regulating services from wetlands (Brander et al., 2013) and non-carbon services from forests (Ojea et al., 2016). The geographic coverage of these meta-analyses is slightly biased towards North America, especially if the study is focused on wetlands (Ghermandi et al., 2008). Most studies have adopted a global coverage while a few have specifically focused on developing or emerging economies (wetlands in developing countries in Chaikumbung et al., 2016; water and recreation services from forests in central America in Ojea et al., 2015; and water services from forests in central and south America in Ojea and Martin-Ortega, 2015).

The present work is, to our knowledge, the first meta-analysis study on the economic valuation of water related ESs focused on the African continent. For this, an original dataset is constructed based on secondary data from published literature, gathering information on the ES, its monetary value, and additional socioeconomic variables following our understanding of the context where the values occur (Section 2.2). A meta analytical model is estimated (Section 3.3) to explain the observed variations in water related ES economic values while controlling for a set of study and context characteristics (Stanley et al., 2013).

2.2. Context for Variable Selection

The selection of potential variables affecting ES values in the meta-analysis is guided by previous studies (e.g. Brander et al., 2012; Ghermandi et al., 2008; Ojea et al., 2010; Richardson and Loomis, 2009) and the understanding of the system and processes where the ESs occur (Fig. 2). The water system (the biome) supports the delivery of ESs (categorized as surface area of production[3] and type of ESs), which yields a benefit to people that can be measured in monetary terms and could potentially depend on the valuation methodology used and the authors' familiarity with the case study area. This monetary or economic value is also dependent on the wider context where it occurs, and will be influenced by context variables on a larger scale, including socio economic and demographic factors (e.g. population, GDP, education level), biodiversity richness, and climate change adaptation readiness and vulnerability. At the same time, the ES economic value also impacts the water system. In turn, it can have a feedback effect on the delivery of ESs (depletion, for example) as well as on the context (e.g. reduced poverty).

Previous meta-analytical approaches for ESs support this reasoning. These studies include variables related to the context, the study and the ecosystem, that are impacting the economic values of the ESs — the dependent variable (Brander et al., 2013; Chaikumbung et al., 2016; Ojea et al., 2010; Ojea and Martin-Ortega, 2015). The next subsection details the selection process for the dependent variable. The full list of variables and their summary statistics are presented in Table 1. In addition, a more detailed definition of each variable is given in Appendix 1.

2.3. Database Building

A peer reviewed literature search was conducted through electronic journal databases including EVRI,[4] SCIENCEDIRECT and Google Scholar during the months of March to August 2014 using all different combinations of the keywords “Economic Valuation”, “Africa”, “Valuation”, “Ecosystem” and “Ecosystem service” in the title, topic and keywords. Studies where collected from 1980 to 2014, as the number of studies using the concept of ESs has increased steadily since the 1990s (Fisher et al., 2009). The grey literature was screened as well using web-based search engines with the same keywords. This was to avoid publication bias and reflect that some ES valuation studies are intended for policy makers and might not be published as journal papers but as reports or policy briefs (Ghermandi et al., 2008; Ojea and Martin-Ortega, 2015). Backward literature search was also performed. The global TEEB valuation database by Van der Ploeg et al. (2010) was screened as it gathers a comprehensive collection of valuation data updated to 2010. 36 data points drawn from 12 studies were extracted from this database.

The valuation of water related ESs in an African country constituted the main criterion for inclusion of a study in the dataset i.e. the study would provide a clear definition of an ES that falls under the definition of water related (i.e. an ecosystem that impacts or is dependent on river flow,[5] cf. Fig. 1), with a stated valuation methodology and value unit. To ensure homogeneity of the dependent variable entries (the ES value), the goods and services valued in the studies had to comply with the MA or TEEB ES definition. Indeed, this ensures that the same shared concept is measured across studies, a key point for a meta-analysis (de Ayala et al., 2014). On a second screening, studies were selected if containing primary valuation data that was explicitly associated to a given service, for a given ecosystem type and elicited with a clearly laid out valuation method.[6] Third, a monetary value per hectare per year unit was adopted to ensure comparability between values, another crucial element when undertaking a meta-analysis (de Ayala et al., 2014). If the data was not readily available in this unit, only values which could be recalculated to the standard unit with information

[3] Standardization by production unit area is necessary to allow comparability across estimates.

[4] Accessible at http://www.evri.ca/en

[5] To check for this, we relied on information given within the paper and complementary cross checks in the scientific literature when necessary.

[6] This information was added as dummy explanatory variables, see Section 3.1.

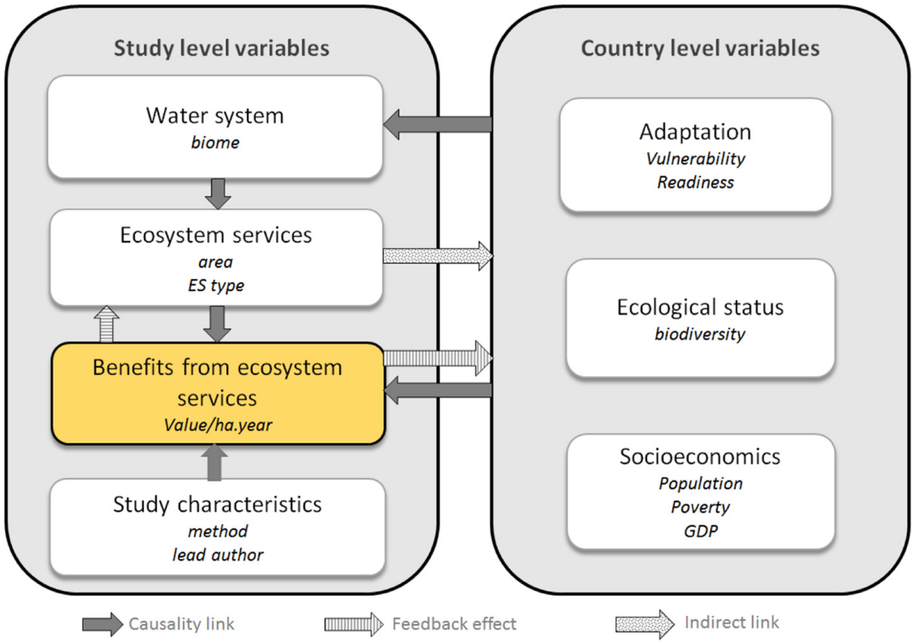

Fig. 2. Potential variables affecting ES values in the meta-analysis.

presented within the studies were included. When necessary, values given for a whole area were divided by the surface area under valuation, if the latter was available in the study. If studies were unclear on how the values were calculated, or the values presented were secondary data or did not provide enough data for standardization per ha, they were excluded from the dataset.

Care was taken to avoid double counting by only reporting disaggregated primary data. As a result, 36 studies out of the 72 derived from the search were not included due to qualitative or secondary valuations, data incompleteness or to the impossibility to convert the value to the standard unit.

All observations were deflated and standardized for comparability to 2014 international USD using the World Bank GDP deflator and purchasing power parity dataset (World Bank, 2015). This is standard procedure due to the various time periods reported and to adjust for the different currencies, income and consumption levels among African countries (Brander et al., 2006; Ojea and Martin-Ortega, 2015; Woodward and Wui, 2001).

The semi-systematic search resulted in an original dataset of 178 ES value observations drawn from 36 studies dating from 1982 to 2014 and spanning 13 countries (see Fig. 3). Data is distributed across Kenya, 32% of the observed values, representing 16% of the studies; Uganda, 23% of total data points representing 27% of included studies; and Tanzania and South Africa, 13% of the reported values, respectively representing 8% and 18% of all studies. East Africa makes up more than half the data points. Other countries provided 19% of data points representing 29% of the studies.

A detailed description of the dataset is presented in Fig. 4. Most observations are provisioning services, such as food, raw materials and freshwater provision (Fig. 4-A). On average, each study provided 5 observations with one outlier study containing 20 observations (Emerton, 2014) and 10 studies providing a single one (e.g. Naidoo and Adamowicz, 2005; Turpie and Joubert, 2001) (see Fig. 4-C). Biomes are represented across all ES categories as observed in Fig. 4-B. Market based methods are the most used methods and are present in every biome (Fig. 4-D). A list of studies included in the analysis is available in Appendix 2 as well as a cross tabulation of the water related ES values per biome in international dollars in Appendix 3.

Fig. 5 provides further descriptive statistics on the values of ESs in the original studies. Values per hectare per year are log-transformed to normalize the data, therefore ranging between negative and positive values in the histograms. Colors represent biome types on the left chart, and ES types on the right chart. The most commonly valued type of biome corresponds to inland wetlands, while the most commonly valued ES type is provisioning services.

3. Model and Specification

3.1. Explanatory Variables

We shall distinguish between study-specific variables that are obtained from the original studies and context variables that are excerpted from global development datasets and from natural index databases. Description, sourcing and summary statistics of all variables used in the model are available in Table 1.

Study-specific variables include the methodology applied in the original valuation exercise and other characteristics of the case studies. Biome (*BIO*) is based on what is defined in the original publication and can be an inland wetland (B_IWT), a coastal wetland (B_CWT), a freshwater system i.e. river, lake, floodplains (B_FWT), woodlands (B_WDL), tropical forest (B_TRO), or grassland (B_GRAS) (Table 1). The number of observations for terrestrial and aquatic ecosystems is 49 and 129, respectively. Both types of biomes present similar average values per hectare with 2014 PPP USD 1457 for terrestrial and 1469 for aquatic biomes. Ecosystem services (*SERV*) are classified following the MA and TEEB categorization into provisioning (PROV), regulating (REG), habitat or supporting (SUPP) and cultural (CULT) services (Table 1). The valuation method (*METD*) can be market-based (METD_M), i.e. direct market pricing, cost based methods, factor income and production function; or non-market based (METD_NM) i.e. contingent valuation and travel cost. The surface area is included in log-transformed hectares (log*HA*) and refers to the area of the ES provision. Finally, information on the lead author is collected to identify any "authorship effect" (Brouwer et al., 1999), recording if the lead author has an affiliation to a research center or an international organization based in Africa (*LEAD*).[7] The literature shows mixed evidence on

[7] It is assumed that affiliation between publication time and research time has not changed.

Table 1
Variable description and summary statistics.

Variable	Type	Description	Variable name	Coding	Number of observations	Mean (Std. Dev.)	Range [Min; Max]
Dependent variable							
lnVAL	Numeral	Natural logarithm of the ES value in international $/ha.year (2014 value)			178	3.84 (3.00)	[-4.35; 11.35]
Explanatory variables							
Study variables							
BIO	Dummy	Type of biome where the service is provided	B_IWT	Inland wetlands (=1)	64	0.36 (0.48)	[0; 1]
			B_CWT	Coastal wetlands (=1)	45	0.25 (0.44)	[0; 1]
			B_FWT	Freshwater[a] (=1)	20	0.11 (0.32)	[0; 1]
			B_WDL	Woodlands (=1)	14	0.08 (0.23)	[0; 1]
			B_TRO	Tropical forest (=1)	27	0.15 (0.36)	[0; 1]
			B_GRAS	Grasslands (=1)	8	0.04 (0.21)	[0; 1]
SERV	Dummy	Type of ecosystem service as per the TEEB classification	PROV	Provisioning (=1)	113	0.63 (0.48)	[0; 1]
			REG	Regulating (=1)	35	0.18 (0.39)	[0; 1]
			SUPP	Supporting (=1)	15	0.08 (0.28)	[0; 1]
			CULT	Cultural (=1)	18	0.10 (0.30)	[0; 1]
logHA	Numeral	Log of the surface area of the ES in hectares	logHA		178	10.35 (3.60)	[-.47[b]; 18.19]
METD	Dummy	Original valuation method used in the primary valuation	METD_M	Market –based methods: direct market price, cost-based, factor income (=1)	158	0.90 (0.31)	[0; 1]
			METD_NM	Non-market- based methods: Contingent valuation and travel cost (=1)	19	0.10 (0.31)	[0; 1]
LEAD	Dummy	Whether the lead author of the study is based in a local or international institution located in Africa.	LEAD	First author based in Africa (=1) other (=0)	178	0.80 (0.40)	[0; 1]
Context variables							
Socio economic and demographic							
PMRY_ENROL	Numeral	Primary school enrolment rate, both sexes, in percentage (World Bank, 2015)			177	102.94 (17.13)	[30.61; 131.27]
GDP	Numeral	GDP per capita in thousands of 2014 PPP USD (World Bank, 2015)			178	3.30 (3.27)	[0.61; 12.3]
POP_R	Numeral	Percentage of rural population (World Bank, 2015)			178	74.86 (12.00)	[23.56; 88.17]
POVTY_R	Numeral	Rural poverty headcount ratio at national poverty line in percentage (World Bank, 2015)			175	50.17 (19.09)	[22.4; 92.2]
Biodiversity							
GEF	Numeral	Composite index by the Global Environmental Facility of relative biodiversity potential for each country. (Pandey et al., 2006)			178	9.37 (6.67)	[0.31; 23.52]
Climate change							
VUL	Numeral	Composite index scoring the vulnerability of each country to climate change. (Notre Dame University, Canada, 2016)			178	1.01 (0.024)	[0.98; 1.11]
READ	Numeral	Composite index scoring the readiness of a country to leverage investment in climate change adaptation policies. (Notre Dame University, Canada, 2016)			178	0.99 (0.06)	[0.88; 1.09]

[a] Freshwater biomes include rivers, lakes and floodplain in line with the categorisation of the TEEB (2010).
[b] The negative values are due to the < 1ha figures for certain ES.

authorship effects. On one side, one can expect that first authors affiliated to an institution located in Africa might be more likely to report higher ES values, as they may have better knowledge of the local context and of the communities where the market and non-market based valuation methods are implemented, therefore providing more accurate and comprehensive estimates. On the other side, in the case of market-based methods, these local authors may have access to finer scale market data that could lower the estimates (Brander et al., 2006), and have better knowledge of cultural and social norms that may help design unbiased non-market preference elicitation approaches.

Context variables related to socio-economic traits, biodiversity level, vulnerability and adaptation to climate change at the national level are also expected to influence the value of water related ESs (see Fig. 2) and were included in the dataset. Each data point for the context variables corresponds to the study's country and year.[8] First, socio-economic and demographic variables such as GDP per capita (*GDP*), education level as the percentage of the population of official primary education age enrolled in primary school (*PMRY_ENROL*), rural population share expressed as the percentage of population living in rural areas (*POP_R*) and rural poverty, the percentage of rural population living below the national poverty lines (*POVTY_R*). The last two variables above are at rural level to reflect that ES provision in the dataset mainly occurs in rural areas. All variables relate to a country's development levels and can potentially explain data heterogeneity. Indeed, it can be expected that more developed countries would tend to present

[8] As an example, for a 2012 study in Uganda, GDP per capita and all other context variables will correspond to year 2012 for Uganda.

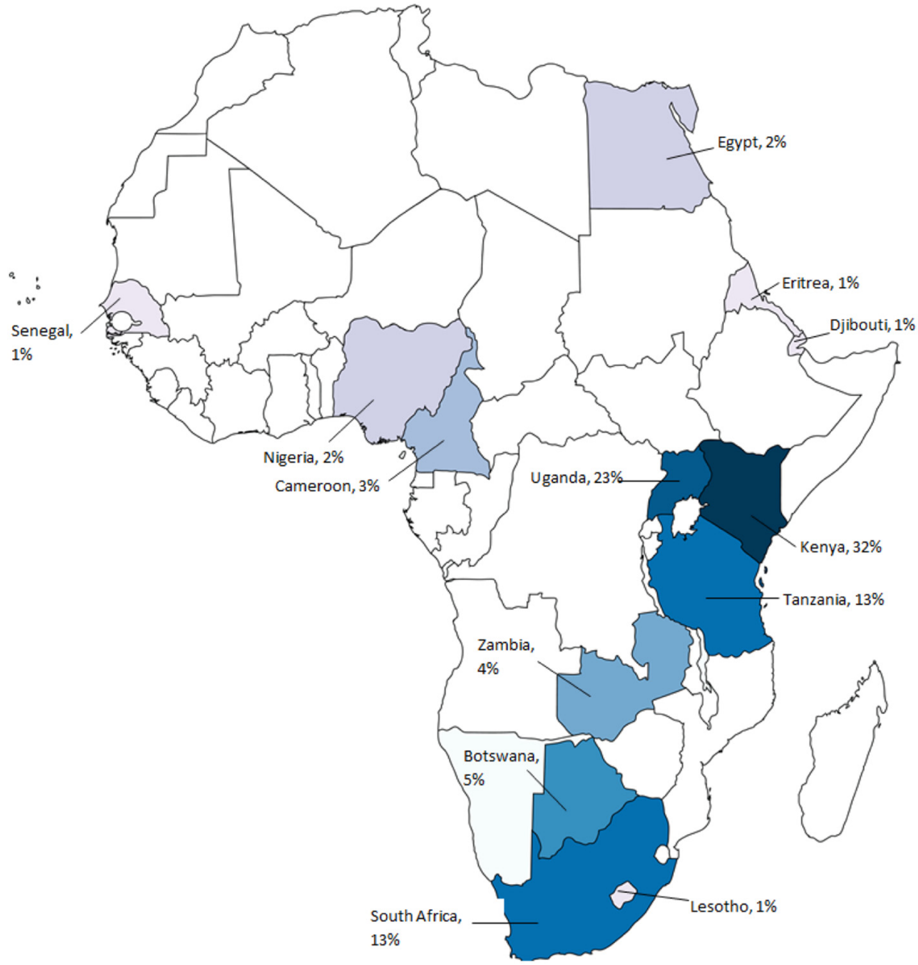

Fig. 3. Geographic distribution of the ES value observations.

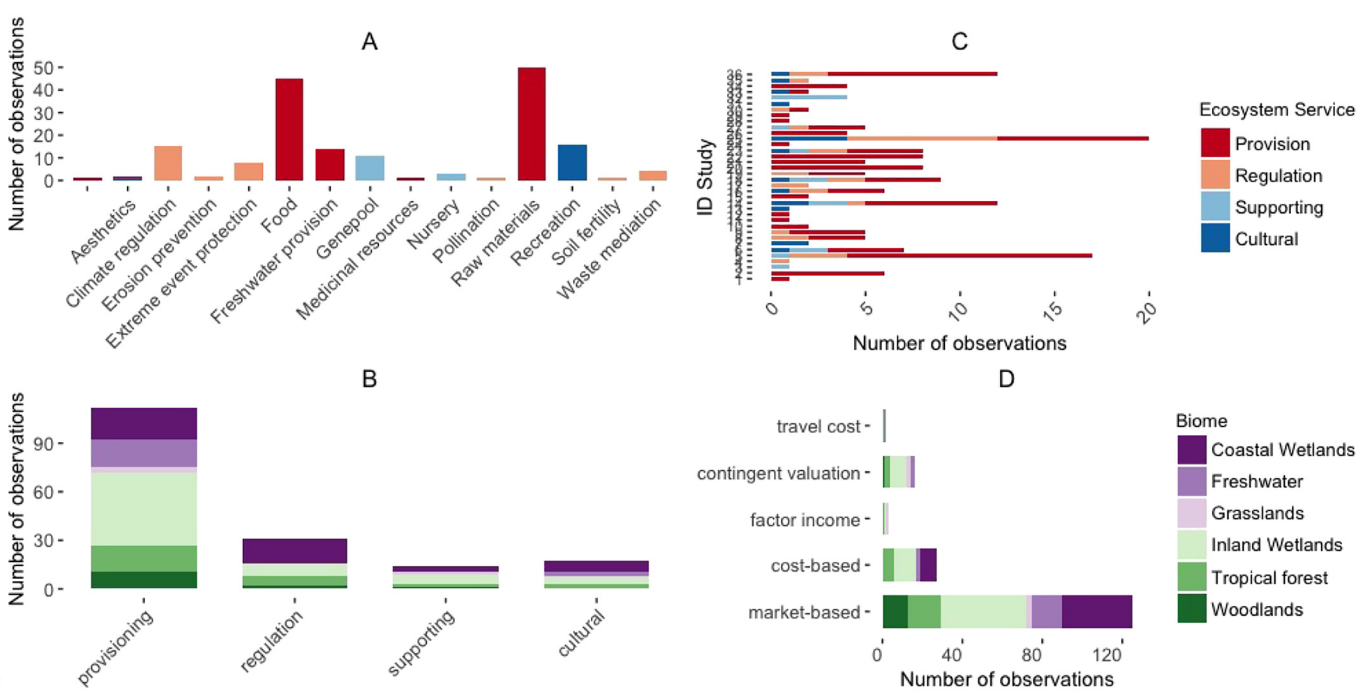

Fig. 4. Summary statistics of the water related ESs in Africa dataset.
Number of observations per sub-type of ESs (A); number of observations per ES type and biome (B); number of observations per original study and ES type (C); and number of observations per methodology and biome (D).

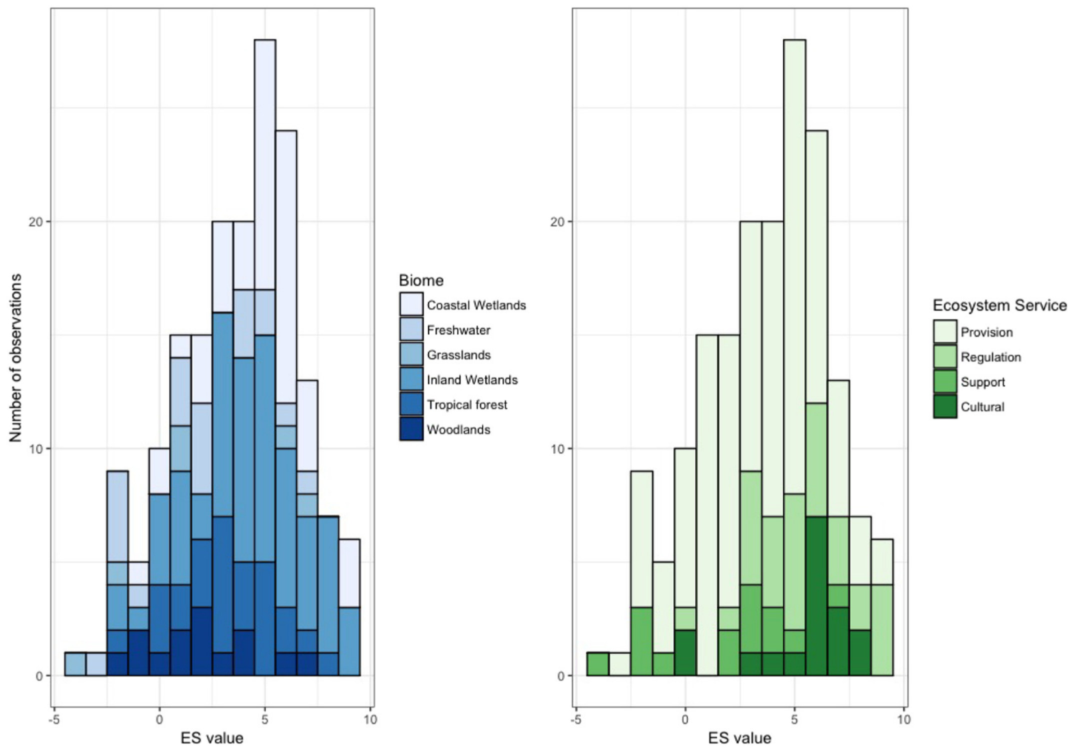

Fig. 5. Histogram of ES values (ln($/ha)) per biome and ES type. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

higher ES values as highlighted in previous meta-analyses (Barrio and Loureiro, 2010; Brander et al., 2006; Ghermandi et al., 2008; Ojea et al., 2010).

Second, a variable reflecting the country's biodiversity status is also included with the biodiversity richness indicator elaborated by the Global Environmental Facility (*GEF*). Indeed, biodiversity fundamentally underpins ecosystems, supporting their capacity to provide services to humans (Cardinale et al., 2012; Ojea et al., 2010). Higher biodiversity levels are associated with water related ESs (Balvanera et al., 2014). However, given that a single service may result from multiple functions, positive and negative effects of biodiversity richness can counteract each other and the resulting net effect is still unknown (Balvanera et al., 2014). Less evidence is available regarding the effect of biodiversity on the economic value of those ESs and the present study wants to contribute in this respect.

Third, climate change indices developed by the Notre Dame University[9] for vulnerability to climate change and readiness to adapt are also considered (*VUL* and *READ*). These indices are included to explore the extent to which ES values are related to climate change vulnerability and potential adaptation leverage in study countries. It is expected that higher ES values are associated with less vulnerable and more ready to adapt countries, as a high value ES can reflect the state of the ecosystems and the associated level of benefits society receives. Each index considers several dimensions of a country's vulnerability and readiness (see Appendix 1). The adjusted for GDP indices are used, they measure the actual performance of the country compared to its expected performance given its GDP. A detailed explanation on all context variables and their sources is available in Appendix 1. Care was taken when selecting the variables to minimize potential collinearity.[10] The tests for collinearity produced a diagnostic of no correlation problem as the Variance Inflation Factors (VIFs) returned values lower than 6 for all variables[11] (Ojea et al., 2010). Correlation coefficients between each variable are available in Appendix 4.

3.2. Model Specification

The dependent variable in the models ($\ln y_{in}$) is a vector of the water related ES monetary values converted to 2014 international US$ per hectare per year. It is expressed in logarithmic terms (see Table 1) based on the analysis of the histograms of the dependent variable in log and non-log form as well as on the result of the Box–Cox model test (Cameron and Trivedi, 2009, chapter 3).[12] Semi-logarithmic regression is also the resulting functional form in previous meta-analyses of ES values (Barrio and Loureiro, 2010; Brander et al., 2007; Johnston et al., 2005; Lindhjem, 2007; Liu and Stern, 2008; Richardson and Loomis, 2009; Rolfe and Brouwer, 2012; Woodward and Wui, 2001). The explicit specification of the meta-regression model can be described as follows:

$$\ln y_{i,j} = \alpha + X_{s,i,j}\beta_s + X_{c,i,j}\beta_c + \varepsilon_i + u_j, \quad (1)$$

where i denotes each specific study ($i = 1, 2, \ldots, N$), j refers to the value estimate reported in the study ($j = 1, 2, \ldots, M_i$), α is the usual constant term or intercept and the β vectors are the coefficients to be estimated in the meta-analysis. Each β coefficient is associated to a type of explanatory variable: either study specific (X_s) or context specific (X_c) (see Table 1). Where each study i provides a single estimate j, then $M_i = 1$ and ε_i collapses into u_j. However, where a study gives more than one value estimate, it is necessary to account for the common error across

[9] ND Gain country index http://index.gain.org/

[10] For example, the adjusted for GDP ND gain indices were chosen over the non-adjusted ones to limit collinearity.

[11] The mean VIF for model 1 is 2.36 ranging from 1.25 to 3.84 and 2.69 for model 2, ranging from 1.36 to 4.95.

[12] The Box–Cox test resulted in a value of −1038 ($\chi^2 = 129.45$) hence the null hypothesis of no difference between semi-log and linear models was rejected at a 1% significance level (i.e. models are significantly different at 99% confidence level in terms of goodness of fit). In addition, we obtain an estimate of $\widehat{\theta} = 0.04$, which gives much greater support for a log-linear (or semi-log) model ($\theta = 0$) than the linear model ($\theta = 1$) (see Cameron and Trivedi, 2009, chapter 3).

Table 2
Models estimated in meta-analysis studies.

Estimation technique	Study
OLS	Brander et al., 2012; Ghermandi et al., 2008; Lindhjem, 2007; Liu and Stern, 2008; Loomis and White, 1996; Ojea et al., 2010, 2016; Richardson and Loomis, 2009; Shrestha and Loomis, 2001
OLS with Huber–White adjusted SE	Barrio and Loureiro, 2010; Brander et al., 2006; Ghermandi and Nunes, 2013; Johnston et al., 2003; Lindhjem, 2007; Woodward and Wui, 2001; Zandersen and Tol, 2009
Weighed OLS with Huber White	Ghermandi and Nunes, 2013
Multi-level OLS	Bateman and Jones, 2003; Brander et al., 2007; Brouwer et al., 1999; Ghermandi et al., 2008; Johnston et al., 2003
GLS	Ojea et al., 2015; Ojea and Loureiro, 2011
Fixed GLS	Ojea and Martin-Ortega, 2015
RE GLS	Chaikumbung et al., 2016; Ojea and Loureiro, 2011
GLS cluster SE	Chaikumbung et al., 2016
Weighed GLS with cluster SE	Chaikumbung et al., 2016; Johnston et al., 2003

Note: some studies estimate more than one model and hence are reported multiple times. Generalized Least Square (GLS), Ordinary Least Squares (OLS), Fixed Effects (FE), Random Effects (RE), Standard Errors (SE).

estimates (u_j) and the individual-specific effect or panel error within a study (ε_i).

3.3. Model Estimation

There are several approaches to estimating this model depending on assumptions regarding the error variance–covariance matrix (Lindhjem, 2007). Table 2 presents the different estimators used in recent meta-analysis literature in environmental economics. These include Weighted Least Squares (WLS), Generalized Least Squares (GLS), explicit specifications of panel models with fixed or random effects, and Ordinary Least Squares (OLS) usually applied with Huber–White adjusted standard errors clustered by study. This last estimator has been most commonly used in the environmental economics literature (see Table 2). Meta-regression models dealing specifically with data heterogeneity, heteroscedasticity and correlated observations are described in Nelson and Kennedy (2009).

Since most studies in the database report more than one monetary value estimate – a panel of observations – estimates from the same study are likely to be correlated. Therefore the meta-regression specification defined in Eq. (1) can be estimated with data-panel structure (Nelson and Kennedy, 2009). The appropriateness of including the study specific error term ε_i was tested by applying the Breusch Pagan Lagrange Multiplier test for random effects (Torres-Reyna, 2007; Zandersen and Tol, 2009).[13] The null hypothesis of no panel effect was rejected at the 5% significance level (χ^2 value of 6.92 with Prob. > $\chi^2 = 0.0043$). In addition, the Hausman test was used to determine whether the random effects model (as opposed to the fixed effects one) is the correct specification. This procedure tests whether a significant correlation between unobserved individual-specific random effects (ε_i) and the explanatory variables (X_i) exists (Cameron and Trivedi, 2009, chapter 8; Wooldridge, 2002, chapter 10). Under the null hypothesis, ε_i in Eq. (1) is purely random, implying that it is uncorrelated with regressors X_i in Eq. (1). The Hausman specification test resulted in a χ^2 value of 11.46 with Prob. > $\chi^2 = 0.32$, yielding to not reject the null hypothesis of non-correlation at the 5% significance level, and therefore supporting the adoption of a random effects model. Cluster-robust standard errors were specified for the random effects panel data models estimated in Section 4 (Cameron and Trivedi, 2009, chapter 8).

4. Results

To better explain the variations in the value observations and check for the robustness of the results obtained, model 1 and extended model 2 with a focus on climate change vulnerability and readiness to adapt are estimated. In addition, cross-products of variables are computed to further interpret the results (Section 4.2).

4.1. Models 1 and 2

Both models are random effects panel data models with cluster-robust standard errors and are estimated in STATA (V.14.1).[14] The two models perform well with reasonable R square for this type of study.[15] The estimated coefficients along with their standard errors and 95% confidence intervals are presented in Table 3:

The coefficients for the dummy variables can be interpreted as constant proportional changes given an absolute change in the variable.

For the study characteristics, freshwater ecosystems (*B_FWT*) resulted into a negative and significant coefficient indicating that freshwater ecosystems have in general, lower ES benefits than other types of biomes in the dataset (grasslands, wetlands, tropical forests and woodlands). Provisioning (*PROV*) and habitat or supporting services (*SUPP*) display significant negative coefficient estimates, with respect to cultural services as the omitted variable (*CULT*). This result indicates that provisioning and habitat services are, in general, related to a lower ES monetary value as compared to cultural services. One explanation could be that revenues from international tourism can be substantially larger than the economic value derived from generally low value provisioning goods (e.g. fish catch), as obtained in other analyses (UNEP, 2010). Indeed, international users may place higher values than local users on services such as tourism, but lower values on regulation services, while local users may do the opposite. Most original studies included in the database did not provide explicit information on end users. However, it can be expected that end users of cultural services are most often foreign visitors, who are wealthier than end users of provisioning and regulating services, who are mostly local communities. Another potential explanation lies in the common use of the market price valuation method for provisioning services valuation, which in the literature is recognized for providing slightly lower estimates than other methodologies (e.g. Brander et al., 2006).

Regarding the valuation method of the primary studies, market-based valuation methods (*METD_M*) seem not to be significantly different from non-market methodologies in our dataset. However, environmental valuation literature generally shows higher values with non-market valuation techniques than with market-based valuation methods (Brander et al., 2006).

[13] This test helps choosing between a random effects regression and a simple OLS regression (Torres-Reyna, 2007).

[14] A GLS model corrected for heteroscedasticity and an OLS with cluster robust standard errors were also estimated for both models (model 1 and model 2) and similar results were obtained in terms of coefficients' significance and behavior.

[15] The overall R-sq is in line with previous published work using the same model (Mattmann et al., 2016) as well as with other model results (Brander et al., 2012, 2006; Brouwer et al., 1999; Chaikumbung et al., 2016; Ghermandi et al., 2008; Ojea et al., 2010, 2015; Shrestha and Loomis, 2001; Woodward and Wui, 2001).

Table 3
Meta-analysis regression model 1 and 2 results.

	Model 1		Model 2	
Variable	Coefficient (Std. Error)	95% CI	Coefficient (Std. Error)	95% CI
B_FWT	-1.086** (0.376)	[-1.822-0.349]	- 1.023** (0.337)	[-1.684-0.363]
PROV	-1.481* (0.859)	[-3.165 0.204]	-1.461* (0.868)	[-3.163 0.241]
REG	-0.166 (0.713)	[-1.564 1.232]	-0.215 (0.727)	[-1.639 1.210]
SUPP	-1.668* (0.951)	[-3.531 0.196]	-1.810** (0.914)	[-3.603-0.019]
logHA	-0.357*** (0.084)	[-.523-0.192]	-0.295*** (0.083)	[-0.458-0.133]
METD_M	-0.617 (0.852)	[-2.288 1.053]	-0.587 (0.859)	[-2.271 1.097]
LEAD	1.949** (0.817)	[0.349 3.550]	2.044** (0.749)	[0.575 3.512]
PMRY_ENROL	-0.035 (0.031)	[-0.096 0.027]	-0.0342 (0.026)	[-0.085 0.017]
GDP	0.311* (0.189)	[-0.060 0.681]	0.367** (0.143)	[0.087 0.648]
POP_R	0.039 (0.044)	[-0.048 0.126]	0.0482 (0.040)	[-0.029 0.126]
POVTY_R	-0.040** (0.017)	[-0.074-0.007]	-0.044*** (0.014)	[-0.071-0.018]
GEF	-0.019 (0.075)	[-0.166 0.128]	-0.139* (0.074)	[-0.284 0.005]
VUL			-46.302*** (12.166)	[-70.147-22.458]
READ			-12.971** (6.840)	[-26.377 0.435]
Constant	9.985** (3.930)	[2.282 17.688]	9.950** (4.165)	[1.785 18.114]
Observations	174		174	
Groups	34		34	
R-sq:	0.3917		0.4818	

Note:
***, **, *: Significance at the 1%, 5% and 10% levels, respectively.
CI: Confidence Interval
Other combinations of variables were tried but gave no significant result
If the regressions had included METD_NM instead of METD_M the coefficients for this variable would have been the reversed of the ones presented here i.e. 0.617 and 0.587 for Model 1 and 2, respectively.

The coefficient for the surface area is also negative and significant, showing that, on average, the larger the area where the ES is produced, the lower the marginal benefit per hectare. This tendency is in line with other studies on environmental valuation and is due to decreasing marginal returns with size (Brander et al., 2006; Chaikumbung et al., 2016; Ghermandi et al., 2008).

The African affiliation of the study lead author (*LEAD*) has a significant and positive impact on the values, which indicates that, on average, valuation studies led by a researcher based on the African continent tend to provide higher benefit estimates. One reason behind this could be that locally based researchers, being more aware of the country and community context, can design and implement questionnaires and focus groups that have greater success in estimating true preferences, which can translate into a higher ES estimate. Further analysis on this effect is needed to understand what particular factors drive this finding, specifically related to the methodologies involved.

ES values greatly differ depending on context characteristics such as GDP and rural poverty. *GDP* per capita is positively related with the ES values, albeit for a very low effect. The rural poverty measure (*POVTY_R*) has, on average, a significant negative effect on ES benefits. Potentially, rural poverty might have a negative impact on the observed values due to the lower market prices practiced in these areas — since the direct market pricing method dominates the dataset (see Fig. 4-D), and the effect of this methodology could be felt in this relationship. Another possible explanation (not in opposition to the previous one) is that a higher poverty rate in a rural setting translates into a higher reliance on natural resources, which subjected to heightened human pressure degrade and provide services of lesser value (either due to lower quality or quantity). This is a two-way effect and the opposite argument could also be made, as having low ES values leads to greater poverty rates. Primary education enrolment (*PMRY_ENROL*) and percentage of rural population (*POP_R*) are on average not significant in either model. Our expectation was that education level might impact positively or negatively ES values but this is not shown in the analysis.

Model 2 results are very similar to model 1 with the exception of the biodiversity indicator (*GEF*) that becomes statistically significant. The negative coefficient for *GEF* suggests a trade-off between a country's biodiversity potential and its water related ES values. Such trade-off has been observed for ES provision (i.e. the service delivery not the value) and biodiversity. For regulating services, Phelps et al. (2012) suggest that there may be important trade-offs between biodiversity level and the delivery of regulating services such as carbon uptake by forests. In the case of provisioning services, it could be expected that ecosystems with higher provisioning service extraction level (food, raw materials, etc.) would be more degraded sites and can be associated with lower biodiversity levels (Butchart et al., 2010; Rey Benayas et al., 2009; Vitousek et al., 1997). However, when it comes to ES values, little evidence exists, and Ojea et al. (2010) show a positive link between biodiversity and provisioning service values. These issues are further investigated in Section 4.2.

Model 2 also shows that the coefficient for vulnerability to climate change of a given country (*VUL*) has a significant negative effect. Higher vulnerability in a country is related to lower water related ES benefits, which may indicate the importance of highly valued ESs for adaptation, as less vulnerable countries have a comparatively smaller adaptation gap (UNEP, 2017). A feedback loop pattern could be at play: an increased vulnerability can in part be due to a degradation of ecosystems, potentially translating into lower values, and a heightened degradation could lead to a reinforced vulnerability. It is to be noted that in our database GDP and vulnerability levels are not correlated[16] (see Appendix 4), suggesting that in our case, GDP levels are not associated with higher or lower vulnerability to climate change. To understand the causal relationship between vulnerability to climate change and ES values, a case study-based analysis where vulnerability and adaptation levels are available at a finer spatial scale would need to be developed. This is not possible with the present dataset, which supports a more exploratory analysis. Our results on *VUL* are in line with the expectations and results from previous literature, showing for some cases (but not at country level) that promoting ESs can be a cost-effective adaptation measure by reducing vulnerability (Doswald et al., 2014; Jones et al., 2012; Munang et al., 2013a).

The readiness to adapt to climate change index (*READ*) displays, on average, a negative relationship with ES values. This suggests that in countries where institutions are less ready and less able to leverage finance for climate change adaptation and implement adaptation policies, the values associated with ESs are higher. This result is somehow surprising and it may be pointing out to a larger issue a country may face. Indeed, the readiness to adapt index is a ranking in absolute that involves economic, institutional and social readiness (see Appendix 1) which mainly rely on non-natural capital. Since ES values mostly contribute to natural capital (Daily et al. 2009), countries may be facing a trade-off between their natural capital and non-natural capital, where the former is related to climate vulnerability and the latter is related to readiness to adapt. Further research is needed to confirm this hypothesis.

[16] VUL and GDP correlation coefficient corresponds to 0.159 at the 5% level (see Appendix 4).

4.2. Interactions

Cross-effects between multiple variables allow further exploring of the results of the meta-models and understand the interactions between variables (Ghermandi et al., 2008). A few interactions were investigated in model 2[17] (see Table 4). This was carried out to: 1) check the interplay between biodiversity levels and the different types of ESs (GEF ∗ REG); 2) explore the authorship effect with the methodologies (LEAD ∗ METD_M); 3) further investigate vulnerability to climate change and ES types (VUL ∗ PROV and VUL ∗ REG); and 4) examine effects of GDP on vulnerability to climate change (VUL ∗ GDP). Results are available in Table 4.

The interactions between *GEF* and the type of ESs (Table 4) further investigate the link between a country's biodiversity potential and its ES values. While biodiversity is affecting ES values in a negative direction in the general model, the cross products of biodiversity and ES values (*GEF ∗ REG* and *GEF ∗ PROV*) are yielding mixed results. There is a positive relation for regulating service values and no significant effect for provisioning. Given these results, a more detailed analysis with study site specific biodiversity levels would be necessary to disentangle the effects of biodiversity on ES values.

The cross-effect of the author's institution (*LEAD*) and the valuation method (*METD_M*) further explains the authorship effect. When the lead author is based in an institution located in Africa and uses market based valuation methods, the ES benefits obtained are lower (*LEAD ∗ METD_M* in Table 4). One reason for this can be access to and understanding of more reliable market data, at a finer scale for a locally based researcher that may avoid overestimation bias. Of course, this interpretation comes with caution as it is unclear whether this explanation applies if the researcher is based in a country different from the one where they do the research. The inverse effect applies and if the lead author uses non-market based methods, the values of the ES benefits will be higher.[18]

The interaction between the vulnerability index and the type of service further informs us about the importance of the different benefits from ESs on adaptation to climate change. Countries more vulnerable to climate change present lower values both for provisioning and regulating ESs (Table 4), while results for cultural and supporting services are not significant. This result reinforces the role of both provisioning and regulating ESs in reducing climate vulnerability. Finally, higher vulnerability to climate change in our sample is related to lower GDP, as the negative coefficient for the cross effect between the vulnerability index and the GDP shows (Table 4).

Table 4
Cross products.

Name of cross product	Coefficient (Std. Error)
*GEF*REG*	0.131 ** (0.061)
*GEF*PROV*	-0.032 (0.083)
*LEAD*METD_M*	-4.475*** (0.976)
*VUL*PROV*	- 41.666 ** (16.835)
*VUL*REG*	- 73.602 *** (16.586)
*VUL*GDP*	-9.121 *** (3.588)

Note: ***, **, *: Significance at the 1%, 5% and 10% levels, respectively. Absence of sign means the interaction was not significant.

5. Discussion

Livelihoods and economies of African developing countries are especially vulnerable to climate change due to their climate sensitive economies that are largely underpinned by ESs and natural resource management (McCarthy, 2001). At a time when the 5th International Panel on Climate Change (IPCC) assessment states with high confidence that “African ecosystems are already being affected by climate change and future impacts are expected to be substantial” (Niang et al., 2014), understanding how managing and enhancing ES values can foster a society's capacity to adapt to climate change is necessary (Doswald et al., 2014). In this context, the present work is novel for two main reasons: 1) to the best of our knowledge, this is the first meta-analysis on benefits from water related ES values in Africa and; 2) we find supporting evidence of a link between the value of water ESs and the vulnerability level of African countries at the national scale.

This work synthesizes existing evidence and effect of factors driving water related ES values in Africa. Results suggest that water related ESs present different values depending on the type of service, biome, lead author's affiliation and socioeconomic factors such as GDP per capita, rural poverty ratio and biodiversity levels, as well as a country's vulnerability and readiness to adapt to climate change. More precisely, the analysis highlights that a country's poverty level and vulnerability to climate change are directly linked to low water related ES benefit values. These interlinks between ES values and – what are essentially – proxy indicators for development levels (poverty, GDP and vulnerability) make the case for ecosystem-based adaptation. Indeed, by bringing evidence of the existing synergy between development levels and the value of water related ESs, the analysis gives quantitative evidence that ecosystem-based adaptation could fulfil its “win–win” promise described in Munang et al. (2013b) and Seddon et al. (2016) of contributing to adaptation to climate change while delivering on the United Nations Sustainable Development Goals (SDGs) (see UN, 2015). However, we only find this link for vulnerability to climate change as the results also show a negative effect of water related ES values on readiness to adapt. More research will be needed to understand what drives this novel result by addressing the question of the extent to which natural capital and non-natural capital are facing inherent trade-offs that might limit the capacity of a country to leverage adaptation action.

This new evidence comes in the context of a recent shift in focus in the adaptation agenda of the international community towards ecosystem-based adaptation. Indeed, under the Paris agreement negotiated within the United Nations Framework Convention on Climate Change (UNFCCC), every five years, countries submit Intended Nationally Determined Contributions (INDCs) that comprise a National Adaptation Plan of Action (NAPA) (see UNFCCC, 2016). The review of the first set of INDCs submitted in 2016 by Seddon et al. (2016) states that the INDCs of 25 African countries have developed detailed NAPAs with tangible ecosystem-based adaptation targets. Now, given how ES values can vary with biomes, type of service etc., research and policy should address who the end users are and how much they benefit from ESs. As ultimately, the end users are key to natural resource management enforcement, especially in rural Africa, and particular attention should be paid to ES end users so that ecosystem-based adaptation policies can affect targeted populations.

6. Conclusions

ESs are important for achieving sustainability and have been successfully used in management and policy around the world. Studies have also highlighted the importance of ESs in adaptation, where investing in recovering and maintaining ESs may be a climate proof

[17] The cross products were included in model 2, one at a time, to analyze each interaction independently.

[18] *LEAD ∗ METD_NM* = 4.475*** (std. error = 0.976).

policy. However, less has been shown on how the values from ESs interact with vulnerability and adaptation to climate change. In this study, we address this last question with a meta-analysis of water related ESs in Africa. We find that higher ES values are related to lower vulnerability to climate change reinforcing the case for ecosystem-based adaptation in Africa. However, we also find that high ES values are related to lower readiness to adapt and further research should look in this direction to explore trade-offs between natural capital and non-natural capital in adaptation.

Further research should address what drives ES values at the local scale by combining observed values with spatial information that can explain variation at a finer scale. This was not possible for exploring biodiversity, adaptation and vulnerability to climate change in the African case studies. But, it may be a necessary approach to understand the specific dynamics of the service users and providers, the area of the ecosystems producing the services and potential seasonal variations in the service provision that may have an effect on their value.

Acknowledgement

This work was undertaken as part of the Water Infrastructure Solutions from Ecosystem Services Underpinning Climate Resilient Policies and Programmes (WISE UP to Climate) project. This project is part of the International Climate Initiative. Bundesministerium für Umwelt, Naturschutz, Bau und Reaktorsicherheit (BMUB) (Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety), Germany supports this initiative on the basis of a decision adopted by the German Bundestag. The authors would also like to thank the Consellería de Educación, Xunta de Galicia for its financial support as well as Anil Markandya, Sébastien Foudi, Marc Neumann, James Dalton and Marta Escapa for their insightful reviews.

Appendix A. Supplementary Material

Supplementary material for this article can be found online at https://doi.org/10.1016/j.ecolecon.2018.03.021.

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